Original investigation

Associations Between Engagement and Outcomes in the SmokefreeTXT Program: A Growth Mixture Modeling Analysis

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Abstract

Introduction: Smoking continues to be a leading cause of preventable death. Mobile health (mHealth) can extend the reach of smoking cessation programs; however, user dropout, especially in real-world implementations of these programs, limit their potential effectiveness. Research is needed to understand patterns of engagement in mHealth cessation programs.

Methods: SmokefreeTXT (SFTXT) is the National Cancer Institute's 6–8 week smoking cessation text-messaging intervention. Latent growth mixture modeling was used to identify unique classes of engagement among SFTXT users using real-world program data from 7090 SFTXT users. Survival analysis was conducted to model program dropout over time by class, and multilevel modeling was used to explore differences in abstinence over time.

Results: We identified four unique patterns of engagement groups. The largest percentage of users (61.6%) were in the low-engagers declining group; these users started off with low level of engagement and their engagement decreased over time. Users in this group were more likely to drop out from the program and less likely to be abstinent than users in the other groups. Users in the high engagers–maintaining group (ie, the smallest but most engaged group) were less likely to be daily smokers at baseline and were slightly older than those in the other groups. They were most likely to complete the program and report being abstinent.

Conclusions: Our findings show the importance of maintaining active engagement in text-based cessation programs. Future research is needed to elucidate predictors of the various levels of engagement, and to assess whether strategies aimed at increasing engagement result in higher abstinence rates.

Implications: The current study enabled us to investigate differing engagement patterns in non-incentivized program participants, which can help inform program modifications in real-world settings. Lack of engagement and dropout continue to impede the potential effectiveness of mHealth interventions, and understanding patterns and predictors of engagement can enhance the impact of these programs.

Introduction

Although smoking rates have declined in the United States, smoking continues to be the leading cause of preventable death.¹ Established

clinical practice guidelines to treat tobacco use and dependence exist; however, services based on these guidelines are often underutilized, particularly among populations at high risk for nicotine dependence, such as young adults, racial/ethnic minorities, adults of

low socioeconomic status, and those with psychiatric comorbidities.² Mobile health (mHealth) smoking cessation programs provide an alternative to traditional delivery models (eg, in-person and quitline services), given the large reach and cost effectiveness of such programs, particularly among hard-to-reach populations.^{3,4} A recent systematic review found that mobile-phone-based interventions for cessation were effective in increasing smoking abstinence.⁵

Although mHealth smoking cessation programs hold promise, user dropout, especially in real-world implementations of these programs, limit their potential effectiveness.⁶ For example, a recent study of the National Cancer Institute's SmokefreeTXT (SFTXT) program, a 6- to 8-week text-messaging smoking cessation program, found that only 53.6% of users completed the full program, and of those who dropped out, approximately half dropped out during the 1st week of the program.⁷

In addition to actively dropping out of the program, users may disengage from the intervention. For example, in text-messaging programs, users may continue to receive messages but stop reading them; they may fail to respond to interactive messages, which are meant to assess progress; and they may not use features of the program that are designed to provide additional support. The Clinical Practice Guideline for Treating Tobacco Use and Dependence: 2008 Update found evidence of a dose-response relationship between program intensity and cessation outcomes.² Being more actively engaged with text-messaging programs may lead to better smoking cessation outcomes. In a randomized controlled trial of Text2Quit, a text-messaging cessation program, users who were biochemically confirmed to be abstainers sent more messages (ie, were more engaged) than those who were not abstainers.⁸

There is a need to better understand patterns of engagement over time in mHealth programs, because that could help define when to provide additional support, which in turn may increase engagement. A recent analysis of the SmokefreeVET text-messaging cessation program, designed for US military veterans, identified five unique patterns of user engagement based on the number of weekly texts that users sent to the program.⁹ The five patterns were high engagement, increasing engagement, rapidly decreasing engagement, delayed decreasing engagement, and low engagement, which varied with respect to the pattern of change in number of weekly texts sent over the 6-week program. Using these unique patterns, the authors found that at the end of the program, users who were more engaged (either high engagement throughout or increasing engagement) had higher smoking abstinence rates than users in the less engaged groups.⁹

Given the limited literature that is currently available on engagement with mHealth resources, more research is needed to understand nuanced patterns of engagement. Understanding these unique patterns of engagement can help inform efforts to tailor intervention content to better meet the needs of different types of users. To explore these issues, we used data from SFTXT because it is available, for free, to US adults who can receive text messages on their cell phones, and therefore is accessible to most adult smokers. Since its inception in 2011, more than 165 000 adult smokers have enrolled in this program. The goal of this study was to identify unique patterns of engagement used with the SFTXT program and to examine the associations between engagement patterns program dropout, and smoking cessation outcomes.

Methods

SFTXT program description

SFTXT is a publicly available text-messaging smoking cessation program, run by the National Cancer Institute, which has been described

in detail elsewhere.¹⁰ SFTXT was developed based on current clinical practice guidelines and provides users with motivational, informational, and cessation-relevant skills-building tips. This 6-week program sends automated text messages to users that are timed, relative to a quit date set by each user. Upon enrolling, users can set their quit date up to 2 weeks in the future, and depending on the date they select, they receive up to 2 weeks of additional preparatory messages that lead up to their quit date. The program sends assessment questions to users at regular intervals to track their smoking status, mood status, and craving levels. Users can also request on-demand assistance by texting one of three keywords (ie, "mood," "crave," or "slip"). In addition, users can reset their quit date during the program if they slip or if they decide they are not ready to quit. They can also drop out of the program at any time by texting "STOP."

Study Population

The study population consisted of SFTXT users who had registered for the program between May 2012 and April 2014, and therefore were part of the real-world implementation of the program; as such, users were not recruited for a specific research study. SFTXT is promoted in several ways; it is highlighted on the Smokefree.gov homepage, it is mentioned in Smokefree social media posts, and links to register for the program are included on partner websites (eg, Centers for Disease Control and Prevention, Food and Drug Administration). Of the total 25 250 users who had the ability to complete the program at the time of the data pull, 21 289 users set a quit date that enabled them to receive the intervention text messages (ie, did not set a quit date in the past; see Figure 1). Of these, 18 078 did not drop out on or before their quit date. Given that the goal of this analysis was to explore patterns of users' engagement with the program, we decided a priori that users who did not send any messages to the program would be excluded from the study, which left 14 215 eligible users. Of these, we selected approximately 50% (7090) as the random sample for this analysis because of the computer capacity and run time needed to conduct the model fit analyses to identify the best model.

Measures

Engagement

Engagement was defined as the number of texts that users sent per week to SFTXT during the 6 weeks of active intervention, beginning with the quit date. Texts that users sent to the program included responses to assessment questions, keywords, and unprompted texts.

Time in Program Variables

For each user, we calculated two variables to measure time spent in the program. The first variable was the number of days enrolled before starting the active intervention. At the time of this analysis, data from subsequent attempts overwrote the data from prior attempts. Because of this, we operationalized the time between when they first enrolled in the program and their most recent quit date as a proxy for multiple attempts, or exposure to program content. The second variable was the number of days active in the program. For users who dropped out by texting "STOP," this variable was the number of days between their quit date and the dropout date. We coded users who did not drop out as being in the program for the full 6 weeks (ie, 42 days).

Smoking Outcomes

Each week during the program, users received a text message asking, "Are you smokefree?" For each week, we categorized users

Figure 1. Inclusion criteria flow chart.

who responded “yes” as *being abstinent* and users who responded “no” as *smoking*. Weekly response rates to the smoking abstinence assessment questions ranged from 36% to 10% declining each week. Therefore, we categorized those who did not respond or who dropped out before the assessment as smoking. To assess whether the interpretation of the findings remained consistent, we included alternative coding of missing data for sensitivity analyses. Specifically, we included an abstinence outcome that consisted only of responders, and an additional abstinence outcome that coded those who had dropped out as smoking and the remaining non-responders as missing. When we categorized only those who dropped out prior to an assessment point as smokers and categorized all others as missing data, 60.2% to 67.2% of the sample was used for each week.

Demographic Information

When enrolling in the program, the program asked users to provide their gender (male/female), age (in years), and smoking frequency (every day, most days, some days, less than that). We dichotomized frequency of smoking into daily smoking (every day) versus not (most days, some days, less than that).

Per National Institutes of Health policy, assessment of quality improvement processes does not require Institutional Review Board approval. Furthermore, there was no personally identifiable information in the data set.

Analyses

Consistent with previous literature, we used latent growth mixture modeling (LGMM) to identify unique patterns of engagement during the 6 weeks of active intervention.¹¹ We assessed the distribution of the number of texts sent each week and found it to be highly skewed, with a high prevalence of zeroes. Thus, to determine the best modeling distributions, we compared negative binomial, Poisson,

and zero-inflated Poisson models, using a Vuong test on null models. The negative binomial model provided the best conceptual and model-based fit, so we used it for subsequent analyses.

We conducted LGMM for the number of texts that users sent each week. For users who had multiple quit attempts, we used data from their most recent quit attempt. Intercepts and slopes were allowed to vary, and we included the number of days enrolled in the program—from enrollment to the most recent quit attempt—as a covariate to account for people re-setting their quit date (a function the program allows). We constructed models ranging from two to six classes using Mplus. We used model fit information (ie, log likelihood, BIC) and VLMR to determine the best fitting number of classes for our sample of users.

After identifying the best fitting class solution, we conducted several analyses in SAS 9.4 to explore differences by class. First, we used chi-square tests and ANOVA to examine differences in demographic characteristics by class. For variables that differed by class, we used unadjusted logistic and linear regression models, as appropriate, to specify where class differences existed. Then, we conducted a survival analysis to model program dropout over time by class. Time in program was censored at 6 weeks. Finally, we used multi-level modeling, with repeated measures of smoking status nested within (non-time-based) individual-level variables, to explore differences in the likelihood of remaining abstinent for each week of the 6-week active intervention. We also predicted end of program abstinence rates from class membership. In both the survival analysis and multilevel modeling analysis, we controlled for users’ number of days enrolled in the program before the quit date, gender, age, and daily smoking status. We also used the Tukey–Kramer method to test differences in mean smoking abstinence rates across classes by week. For the smoking abstinence analysis, we conducted sensitivity analyses to assess whether the interpretation of the findings remained consistent.

Results

Growth Mixture Modeling

We found that both four- and five-class models were adequate for the data; so based on an assessment of BIC, overall model fit, and desire for parsimony, we selected a four-class model as the final model. The four-class model produced trajectories that corresponded to high engagers–declining (HED), defined as users who started with high-engagement levels but whose level of engagement decreased over time ($n = 864$, 12.2%); high engagers–maintaining (HEM), defined as users who started with higher engagement, and though their levels decreased over time, they remained greater than other groups ($n = 938$, 13.2%); low engagers–declining (LED), defined as users who started with low levels of engagement that decreased over time ($n = 4367$, 61.6%); and low engagers–maintaining (LEM), defined as users who started with low levels of engagement but maintained some engagement over time ($n = 921$, 13.0%; see Figure 2).

User Characteristics

Overall, 64.3% of users were female ($n = 4494$), 91.9% were daily smokers ($n = 6210$), and the mean age was 34.3 years (see Table 1). There were no significant differences in gender across classes. In fact, the only demographic characteristic that was significantly different was that users in the HEM class were less likely to be daily smokers and were slightly older than users in the other three classes ($ps < .01$).

Program Retention

Compared with users in the LED class, users in the other classes had a lower hazard of dropping out before completing the 6-week

program (LEM: HR = 0.17; HED: HR = 0.74; HEM: HR = 0.11; $Ps < .001$; see Figure 3). Among those who dropped out before completing the program, those in the HEM class and the LEM class remained in the program for longer (an average of 32.7 days and 30.7 days, respectively) than those in the HED class (an average of 5.7 days) and LED class (an average of 5.3 days) (data not shown).

Smoking Cessation Outcomes

There was a main effect of intervention week on smoking abstinence; that is, the further users were from their quit date, the more likely they were to smoke ($F = 212.40$, $p < .001$; see Figure 4). There was also a main effect for class ($F = 2269.13$, $p < .001$) and an interaction between class and week ($F = 36.79$, $p < .001$). Abstinence rates for each class were significantly different from one another at each week ($p < .001$), except for abstinence rates among users in the HED and LED classes, whose abstinence rates were approximately the same for weeks 5 and 6. At the end of treatment (week 6), 44.9% of users in the HEM class were abstinent as compared with 9.0% in the LEM class and 0.8% in the HED and LED classes.

In our sensitivity analyses, the pattern of abstinence rates over time for each class was consistent with the primary analysis (data not shown). There was a main effect for intervention week and class and the interaction between week and class that mirrored that of the primary analysis. At end of treatment, when users who dropped out were categorized as smokers on all assessments after their drop out date and all other non-responders were not included, the abstinence rates were 68.7% (HEM), 22.9% (LEM), 1.2% (HED), and 1.1% (LED). When only responders were included, abstinence rates were 88.1% (HEM), 52.2% (LEM), 44.3% (LED), and 43.8% (HED).

Figure 2. Four-class LGMM with average weekly texts sent.

Table 1. Descriptive Characteristics of SFTXT Users Overall and by Class

User Characteristics	HED ($n = 864$)	HEM ($n = 938$)	LEM ($n = 921$)	LED ($n = 4367$)	Total ($n = 7090$)
% female (n)	67.5 (576)	65.5 (607)	61.9 (563)	63.9 (2748)	64.3 (4494)
% daily smokers ^a (n)	92.2 (763)	88.4 (794)	91.7 (803)	92.6 (3850)	91.9 (6210)
Mean age ^a (SD)	35.4 (11.5)	37.3 (11.8)	35.1 (11.4)	33.2 (10.8)	34.3 (11.2)

^a $p < .01$

^aAdjusted for age, gender, and days enrolled prior to beginning the active intervention.

Figure 3. Survival analysis of days in program by class. Adjusted for age, gender, and days enrolled prior to beginning the active intervention.

Figure 4. Weekly abstinence rates by class. Adjusted for age, gender, and days enrolled prior to beginning the active intervention.

Discussion

Key Findings

This study applied growth mixture modeling to estimate unique patterns of engagement with a text-message smoking cessation program. There were four unique patterns of engagement groups identified: HEM, HED, LEM, and LED. The largest percentage of users (61.6%) were in the LED group, with users in this group being more likely to drop out from the program and less likely to be abstinent than users in the other groups. Users in the HEM group (ie, the smallest but most engaged group) were less likely to be daily smokers at baseline and were slightly older than those in the other groups. Most mHealth research studies include daily smoking as an inclusion

criteria and, therefore, cannot explore daily smoking status as a predictor of program outcomes. Although baseline smoking status and age are not modifiable, SFTXT intervention content can be tailored, based on these characteristics, to help improve engagement among those who are more nicotine-dependent and younger. For example, messages tailored for nicotine-dependent smokers might focus on troubles with cravings or withdrawal symptoms, especially early on in the quit attempt, and provide tips for managing cravings. Research in this area should also consider factors beyond baseline characteristics and consider mixed-methods inquiry into the reasons that users engage or disengage with text-messaging programs.

Although users in the more consistently engaged groups (HEM, LEM) had higher rates of smoking abstinence at the end of treatment

than those in the less engaged groups, the differences in abstinence rates between even these two groups was large (HEM, LEM; 44.9% vs. 9%, respectively). Changes to the program that increase engagement even slightly could potentially improve program outcomes. In addition to encouraging engagement early on, promoting ongoing engagement is also important. Although the HED class had a similar average number of texts in the first week as the HEM group, a lack of ongoing engagement was associated with an end of program abstinence rate (0.8%) that was identical to the LED group that had low engagement throughout.

Often, engagement has been considered as a single construct (eg, total # of texts sent by a user) and has not been operationalized consistently across studies.¹² Our findings suggest that the relationship between user engagement and abstinence is multifaceted and that increasing initial engagement and prolonging ongoing engagement among users could lead to improved smoking cessation outcomes. However, there is little research on strategies that improve engagement with a text-message based intervention, and the impact of increasing engagement on cessation has not yet been assessed.

Patterns of engagement were also associated with program dropout. Users who interacted with the program by sending more weekly texts were more likely to complete the full 6 weeks of treatment. Dropout patterns for the two maintaining groups (HEM, LEM) mirrored each other, with gradual dropout over time, as did dropout patterns for the two declining groups (HED, LED), with steeper rates of dropout earlier on. This finding suggests that initial engagement alone might not be a strong indication of successfully staying in a text-based smoking cessation program. Further, across groups, dropout rates were higher during the first couple of weeks of the intervention and then leveled off, indicating a need for targeted efforts to reduce dropout early on.

Comparisons to Previous Studies

To our knowledge, only one study has used growth mixture modeling to determine unique patterns of engagement with a text-messaging smoking cessation program.⁹ The number of user classes and trajectories of engagement in the SFTXT user population differed slightly from the previous study conducted with the SmokefreeVET program.⁹ Although similar patterns between the two text-messaging cessation programs might be expected, there were several unique aspects of each program that could have led to the slightly different patterns of engagement. SmokefreeVET is specifically designed for military veterans, and as such, both the recruitment strategies (eg, referrals from Department of Veterans Affairs [VA] doctors) and the intended audience (eg, primarily male) differ from that of the SFTXT program, which is for adult smokers in the general population. Although in both studies, the largest percentage of users were in the low engagement groups, a larger percentage of SmokefreeVET users than SFTXT users were in a high engagement group. This may be because the SmokefreeVET program has a more specified audience and has more direct connections to users' health care system (eg, VA doctors might be reinforcing and following up with patients on cessation attempts) and associated resources (eg, access to nicotine replacement therapy), neither of which are components of the SFTXT program.

Consistent with other studies, engagement was defined as the number of texts users sent to the program each week, which is a robust measure of engagement. Nonetheless, there are other aspects of engagement (eg, reading the texts sent by the program, clicking on links in texts for additional information) that are associated with

user outcomes but that were not captured in this operationalization of engagement.¹³ Specific facets of engagement can influence program outcomes differently. For example, Heminger and colleagues found that participants who dropped out of their text-messaging program were 76% less likely to be abstinent at 6 months as compared with those who did not drop out.¹⁴ They also found that time in program and program dose (ie, the amount of program content received) did not predict abstinence rates; however, the number of texts that participants sent did. In combination with the findings from our study, reducing dropout rates and prompting users to actively engage (ie, text) with the program are two aspects of engagement that should be targeted to potentially improve program outcomes.

Limitations

This study did have limitations that need to be considered. First, the indicators we used to create the classes (ie, weekly text for each of 6 weeks) are from the same time period as the outcome variables of interest (eg, time in program, smoking status). Ideally, indicators for latent classes would be collected earlier; our underlying assumption was that these classes existed before program engagement began and are program specific. Second, we focused on short-term (ie, end of 6-week treatment) outcomes rather than longer-term cessation outcomes, so we cannot infer the potential long-term relationship between engagement and smoking outcomes. We chose to focus on short-term outcomes, in part, because a primary aim of the study was to understand differences in engagement during the program itself as a potential predictor of program dropout. In addition, as the user data analyzed in this study were from a publicly available program, not from incentivized randomized controlled trial participants, there was a high rate of loss to follow-up at extended assessment intervals.⁷ Third, in our primary analysis, we categorized users who did not respond or users who dropped out prior to a given assessment point as smokers. However, we also conducted sensitivity analyses in which we compared smoking status operationalized in different ways (eg, we included only responders; we categorized only those who opted out prior to an assessment point as smokers and categorized all others as missing data, etc.), and the interpretation of findings remained the same. Finally, a limitation of using program data as opposed to research data is that, by design, there is limited data on user characteristics, like motivation to quit smoking, age when the user started smoking, or use of other cessation aids while using SFTXT; thus, we could not adjust for all potential confounders in the analyses.

Summary and Future Directions

Despite these limitations, this study was a first step in understanding engagement patterns among users of a free and publicly available mHealth smoking cessation program. Our findings show the importance of maintaining engagement in text-based cessation programs and identified several important areas for future research that can help mHealth researchers create more successful behavior change interventions. For example, additional information is needed on the characteristics of users who are more or less likely to engage with mHealth interventions. To begin to address this concern, we included additional questions on the SFTXT enrollment form. These questions capture more detailed data on users (eg, nicotine dependence, self-efficacy for quitting, motivation for quitting, time spent around other smokers, etc.) that may be associated with program engagement and dropout. Furthermore, future studies should explore the effects of strategies designed to increase and maintain engagement

on cessation outcomes. We added text messages that target relevant predictors of dropout to the SFTXT program to assess whether tailored program content affects engagement. The specific effect of such changes on users may differ depending on their engagement patterns, and future research can examine how these changes may alter patterns of engagement.

The current study enabled us to investigate differing engagement patterns in non-incentivized program participants, which can help inform program modifications in real-world settings. Lack of engagement and dropout continue to impede the potential effectiveness of mHealth interventions, and understanding patterns and predictors of engagement can enhance the impact of these programs.^{15,16}

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Declaration of Interests

None declared.

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